Exploration of the effect of electronic technology paradigm shift under the theory of innovation diffusion:

Q Firm vs. W Firm Correlation Comparison

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Abstract: The advancement of generative AI and the advent of specific applications of related AI software and hardware have brought about a paradigm shift in technology. This paradigm shift has accelerated the progress of human technology and solved many problems quickly and efficiently.We also look forward to newer inventions and discoveries. This study starts from the theory of innovation diffusion, empirically puts these AI technology chains and projects into the model, resulting in diffusion and derivatives, and such a paradigm shift infers greater benefits, and by machine learning and deep learning methods, Verify possible future scientific scenarios, and spread and amplify possible inferences from a scientific perspective. And use this inference to illustrate the amazing performance and results of AI electronic technology. The paradigm shift will accelerate the development of AI

electronic technology. and generate a powerful AI hardware supply chain. rapid diffusion effect: AIGC→GPU→GPU Mainboard →AI Server→Cooler→ABF→AI power supply→Chassis. And use ML method to compare W company with Q company. Some correlation features were found. NLP combined with digital reporting.

Keywords: AIGC ; GPU ; AI Server ; AI Server Supply Chain; Innovation Diffusion; Paradigm Shift

1. Introduction

A paradigm shift is a fundamental change in the basic concepts and experimental practices of a scientific discipline. It is a concept in the philosophy of science that was introduced and brought into the common lexicon by the American physicist and philosopher Thomas Kuhn. Even though Kuhn restricted the use of the term to the natural sciences, the concept of a paradigm shift has also been used in numerous non-scientific contexts to describe a profound change in a fundamental model or perception of events. Kuhn presented his notion of a paradigm shift in his influential book The Structure of Scientific Revolutions (1962). Kuhn contrasts paradigm shifts, which characterize a Scientific Revolution, to the activity of normal science, which he describes as scientific work done within a prevailing framework or paradigm. Paradigm shifts arise when the dominant paradigm under which normal science operates is rendered incompatible with new phenomena, facilitating the adoption of a new theory or paradigm[1]. Diffusion of innovations is a theory that seeks to explain how, why, and at what rate new ideas and technology spread. The theory was popularized by Everett Rogers in his book Diffusion of Innovations, first published in 1962.[2] Rogers argues that diffusion is the process by which an innovation is communicated over time among the participants in a social system. The origins of the diffusion of innovations theory are varied and span multiple disciplines. Rogers proposes that five main elements influence the spread of a new idea: the innovation itself, adopters, communication channels, time, and a social system. This process relies heavily on social capital. The innovation must be widely adopted in order to self-sustain. Within the rate of adoption, there is a point at which an innovation reaches critical mass. In 1989, management consultants working at the consulting firm Regis Mckenna Inc. theorized that this point lies at the boundary between the early adopters and the early majority. This gap between niche appeal and mass (self-sustained) adoption was originally labeled "the marketing chasm"[3]. The categories of adopters are innovators, early adopters, early majority, late majority, and laggards.[4] Diffusion manifests itself in different ways and is highly subject to the type of adopters and innovation-decision process. The criterion for the adopter categorization is innovativeness, defined as the degree to which an individual adopts a new idea.

From the end of November 2022, openAI proposes chatgpt, Generative AI thus produces great applications, and generate enormous computing demands. From March 2023, GPU high-efficiency computing will become the core of hardware technology, Major software companies are developing AIGC applications. More high-speed data centers are needed, AIGC (AI Generated Content) and GPU across “chasm”, Quick “Paradigm Shift”, And form a strong AI supply chain.

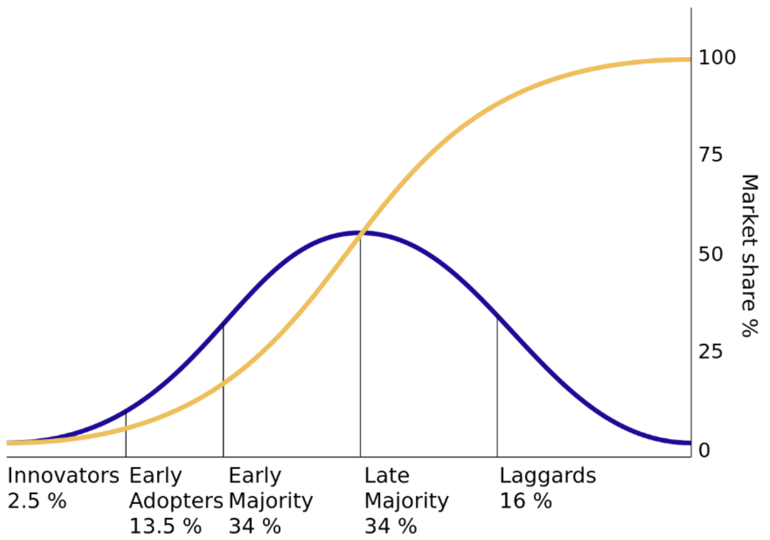


Figure 1 Remarks: The diffusion of innovations according to Rogers. With successive groups of consumers adopting the new technology (shown in blue), its market share (yellow) will eventually reach the saturation level. The blue curve is broken into sections of adopters.

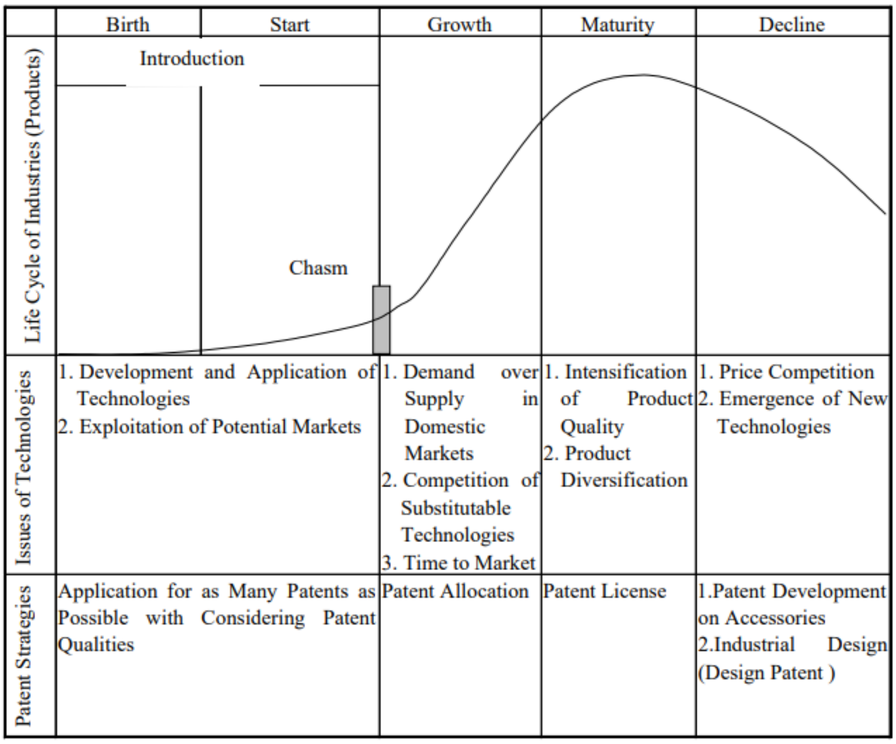


Figure 2 AIGC (AI Generated Content) and GPU across “chasm”. schematic diagram.

2. Related Work: Explaining this paradigm shift with Explainable AI

XAI stands for explainable Artificial Intelligence. It refers to the ability of artificial intelligence (AI) systems to provide transparent explanations of their decision-making process and outcomes in a way that humans can understand. The goal of XAI is to make AI systems more transparent, trustworthy, and accountable.XAI techniques include methods for visualizing and interpreting the inner workings of AI models, as well as techniques for generating natural language explanations of the AI's decision-making process. XAI is an active area of research in AI and has become increasingly important as AI systems are deployed in more and more critical applications.

The main purpose of applying XAI is to answer one or more of the main seven goals, including reliability, usability, trust, fairness, privacy, causality, and transparency. Therefore, XAI has been used across different deep learning models in order to further justify the proposed classification within a specific domain’s functionality, as well as the overall reliability of Deep Learning and Machine Learning . As previously stated, machine learning has been applied for various purposes. One such application—sentiment analysis—involves determining the polarity of a text as negative, neutral, or positive. Throughout previous research, sentiment analysis has been applied through the use of ML and DL models for accurate polarity classification in different domains and languages.XAI has been studied to apply artificial intelligence with more transparency while maintaining high performance [5].NLTK is intended to support research and teaching in NLP or closely related areas, including empirical linguistics, cognitive science, artificial intelligence, information retrieval, and machine learning.Sentiment analysis research depends on data originating from news,articles,papers...etc. The Natural Language Toolkit, or more commonly NLTK, is a suite of libraries and programs for symbolic and statistical natural language processing (NLP) for English written in the Python programming language. It was developed by Steven Bird and Edward Loper in the Department of Computer and Information Science at the University of Pennsylvania [6]. In March 2023, the author found that a paradigm shift will occur. So use NLP and machine learning methods to study GPU Nvidia.

Explainable AI (XAI), also known as Interpretable AI, or Explainable Machine Learning (XML),[7] is artificial intelligence (AI) in which humans can understand the reasoning behind decisions or predictions made by the AI.[8] It contrasts with the "black box" concept in machine learning, where even the AI's designers cannot explain why it arrived at a specific decision.[9][10] XAI hopes to help users of AI-powered systems perform more effectively by improving their understanding of how those systems reason.[11] XAI may be an implementation of the social right to explanation.[12] Even if there is no such legal right or regulatory requirement, XAI can improve the user experience of a product or service by helping end users trust that the AI is making good decisions. XAI aims to explain what has been done, what is being done, and what will be done next, and to unveil which information these actions are based on.[13] This makes it possible to confirm existing knowledge, challenge existing knowledge, and generate new assumptions.[14]

3. Methodology

3.1 Research framework(Figure 3)

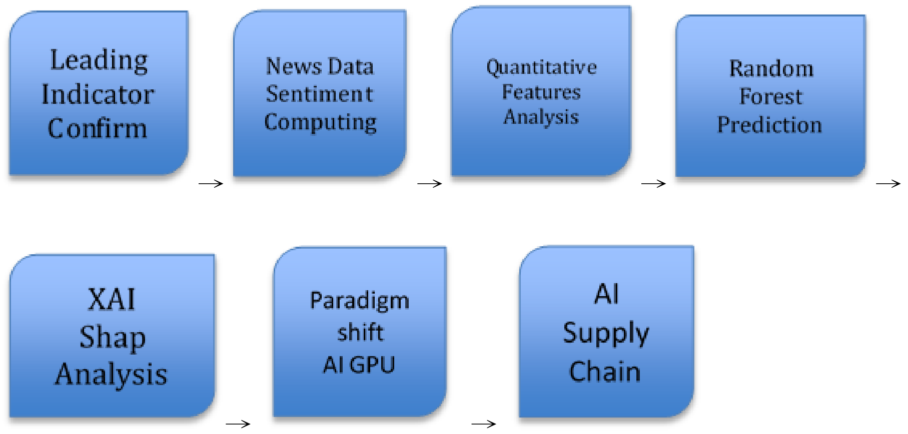


Figure 3

3.1.1 Leading indicator

The PHLX Semiconductor Sector (SOX) is a Philadelphia Stock Exchange capitalization-weighted index composed of the 30 largest U.S. companies primarily involved in the design, distribution, manufacture, and sale of semiconductors. It was created in 1993 by the Philadelphia Stock Exchange.

3.2. Sentiment Analysis Score

As we mentioned earlier, we applied the sentiment analysis using the sentiment analyzer based on the NaiveBayesAnalyzer. This technique helps to detect the text polarity and classify it into three different classifications: positive, neutral, or negative. we used the following thresholds to classify the scores of sentiment analysis:

• Positive (score between 0.05 and 1);
• Negative (score between −0.05 and −1);
• Neutral (score between −0.05 and 0.05).

Data Analysis through NaiveBayesAnalyzer

3.3. Data Source and Collection

(Financial News Reviews A) 2023.03.23

The global AI (Artificial Intelligence) war has begun, and various technology giants have continuously invested in related fields. In this wave of excitement, the American graphics chip giant Nvidia has emerged as a standout performer, with its stock price rising for 8 consecutive days, equaling the longest winning streak since 2007.

(Financial News Reviews B) 2023.03.23

With the launch of the chatbot ChatGPT by technology startup OpenAI in late November last year, a new wave of enthusiasm for generative AI has been sparked globally, and discussions have been raised about how this technology will change services such as internet search engines, product design, text creation, and program coding. This new technology requires powerful computing capabilities in data centers, and Nvidia has already established a huge and constantly growing business in graphics processors and software designed specifically for AI applications.

3.4. Relationship

Semantic similarity is a metric defined over a set of documents or terms, where the idea of distance between items is based on the likeness of their meaning or semantic content as opposed to lexicographical similarity. These are mathematical tools used to estimate the strength of the semantic relationship between units of language, concepts or instances, through a numerical description obtained according to the comparison of information supporting their meaning or describing their nature.

3.5 Naive Bayes classifier

Naive Bayes classifier is a probabilistic machine learning algorithm that is commonly used for classification tasks. It is based on Bayes' theorem, which is a fundamental concept in probability theory. The Naive Bayes classifier assumes that the presence or absence of a particular feature in a class is independent of the presence or absence of other features.

The basic idea behind Naive Bayes is to calculate the probability of a particular class given a set of input features. To do this, the algorithm first calculates the prior probability of each class, which is the probability of the class occurring without considering the input features. It then calculates the likelihood of the input features given each class, which is the probability of observing the input features given that the class is true. Finally, it uses Bayes' theorem to calculate the posterior probability of each class given the input features.

The "Naive" in Naive Bayes refers to the assumption that the features are independent of each other. This assumption simplifies the calculation of the likelihood probabilities and makes the algorithm computationally efficient. Although this assumption may not always hold in practice, Naive Bayes has been shown to perform well in many real-world applications, especially in natural language processing tasks such as text classification and spam filtering.

3.5.1 Naive Bayes equation

The Naive Bayes classifier equation is derived from Bayes' theorem and assumes that the input features are conditionally independent given the class variable. The equation can be written as follows: (equation 1)

$$P(C|X) = P(C) * P(X|C) / P(X) \qquad \text{equation 1}$$

where:

P(C|X) is the posterior probability of class C given input features X.
P(C) is the prior probability of class C.
P(X|C) is the likelihood of observing the input features X given that the class is C.
P(X) is the probability of observing the input features X.

To classify a new observation, the algorithm calculates the posterior probability for each possible class and assigns the observation to the class with the highest probability. The prior probability of each class can be estimated from the training data, and the likelihood probabilities can be estimated using various techniques, such as maximum likelihood or Bayesian estimation.

3.6 SHAP

SHAP (SHapley Additive exPlanations) is a popular XAI method that can be used to explain the output of a machine learning model. It is based on game theory and provides a way to assign "importance" values to each feature or input variable in a model.

The SHAP method calculates the contribution of each input feature to the final output of a model by considering all possible combinations of features and their impact on the output. It then assigns an importance score to each feature based on how much it contributes to the model's prediction.

By using SHAP, we can gain insights into how a model is making decisions and identify which features are the most important in driving those decisions. This can help improve the transparency and trustworthiness of AI systems, and enable users to better understand and interpret the results of machine learning models.

3.7 Random Forest

Breiman (2001) developed random forest as an ensemble technique to handle supervised classification. Using supervised learning algorithms, random forests build decision trees with training sets, in order to improve their accuracy. Random forest uses the bagging method to build ensembles of decision trees. RF generates a variety of trees from bootstrapped subsamples (random samples drawn with replacement) of coaching information. It is historically determined, based on finding a split attribute that is simple among a narrower set, what a tree seems to be. Consequently, randomly generated trees are less related, since they make the same kinds of prediction errors and may overfit the model. The trees in less related trees will be incorrect in some cases, but the correct ones, and the trees collectively, should move in the right direction, since as they are closely related, the outputs are summed up for the final prediction. Random forest (RF) is a collaborative model. The first step is selecting features, followed by classifying them. Random forests create multiple decision trees from random subsets of data. The major advantage of random forests over other traditional classifiers is their lower classification errors. When dealing with large datasets, RF requires too much computation

4. Results and Findings

4.1. Sentiment Analysis Results

(Financial News Reviews A) 2023.03.23

```
conda install -c conda-forge textblob
from textblob import TextBlob

text='''	The global AI (Artificial Intelligence) war has begun, and various technology giants have continuously invested in related fields. In this wave of excitement, the American graphics chip giant Nvidia has emerged as a standout performer, with its stock price rising for 8 consecutive days, equaling the longest winning streak since 2007.
'''
```

```
blob=TextBlob(text)
blob
```

Out[18]: TextBlob(" The global AI (Artificial Intelligence) war has begun, and various technology giants have continuously invested in related fields. In this wave of excitement, the American graphics chip giant Nvidia has emerged as a standout performer, with its stock price rising for 8 consecutive days, equaling the longest winning streak since 2007. ")

```
blob.sentiment
```

Out[19]: Sentiment(classification='pos', p_pos=0.9132790148342463, p_neg=0.08672098516576003)

```
for sentence in blob.sentences:
    print(sentence.sentiment)
```

Sentiment(classification='pos', p_pos=0.8193990382212176, p_neg=0.18060096177878734)
Sentiment(classification='pos', p_pos=0.7094793640404503, p_neg=0.2905206359595532)

(Financial News Reviews B) 2023.03.23

text=''' With the launch of the chatbot ChatGPT by technology startup OpenAI in late November last year, a new wave of enthusiasm for generative AI has been sparked globally, and discussions have been raised about how this technology will change services such as internet search engines, product design, text creation, and program coding. This new technology requires powerful computing capabilities in data centers, and Nvidia has already established a huge and constantly growing business in graphics processors and software designed specifically for AI applications. '''

```
blob=TextBlob(text)

blob
```

Out[23]: TextBlob(" With the launch of the chatbot ChatGPT by technology startup OpenAI in late November last year, a new wave of enthusiasm for generative AI has been sparked globally, and discussions have been raised about how this technology will change services such as internet search engines, product design, text creation, and program coding. This new technology requires powerful computing capabilities in data centers, and Nvidia has already established a huge and constantly growing business in graphics processors and software designed specifically for AI applications. ")

blob.sentiment

Out[37]: Sentiment(classification='pos', p_pos=0.9999967748992359, p_neg=3.22510076807198e-06)

```
for sentence in blob.sentences:
    print(sentence.sentiment)
```

Sentiment(classification='pos', p_pos=0.9999981736049944, p_neg=1.826395007297365e-06)
Sentiment(classification='pos', p_pos=0.5308129864713492, p_neg=0.46918701352864806)

Remarks:
(Financial News Reviews A)
Sentiment(classification='pos', p_pos=0.9132790148342463, p_neg=0.08672098516576003)
(Financial News Reviews B)
Sentiment(classification='pos', p_pos=0.9999967748992359, p_neg=3.22510076807198e-06)

4.2. Similarity

pip install spacy
import spacy

nlp=spacy.load('en_core_web_sm')

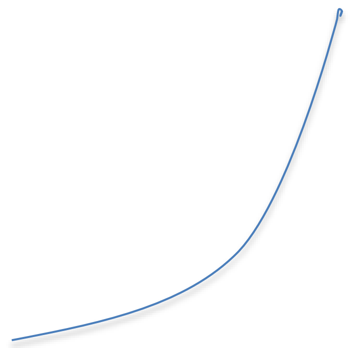
A_doc=nlp(" The global AI (Artificial Intelligence) war has begun, and various technology giants have continuously invested in related fields. In this wave of excitement, the American graphics chip giant Nvidia has emerged as a standout performer, with its stock price rising for 8 consecutive days, equaling the longest winning streak since 2007.   ")

B_doc=nlp("   With the launch of the chatbot ChatGPT by technology startup OpenAI in late November last year, a new wave of enthusiasm for generative AI has been sparked globally, and discussions have been raised about how this technology will change services such as internet search engines, product design, text creation, and program coding. This new technology requires powerful computing capabilities in data centers, and Nvidia has already established a huge and constantly growing business in graphics processors and software designed specifically for AI applications.   ")

print(A_doc.similarity(B_doc))
0.8107878958004379

4.3 Nvidia GPU: Specific birth paradigm shift on 2023/5/30

Figure 4 is the author's original idea: Rapid Diffusion of Innovation



“Chasm”

Figure 4   Rapid Diffusion of Innovation

4.4 AI supply chain reasoning

AIGC→GPU→GPU Board →AI Server→Cooler→ABF→AI power supply→Chassis

4.5 Q Firm AI Server Case

Figure 5

From May 12th to July 21th(share price):

sample_data={'price_score':[101.5,97.6,101,100.5,102.5,109,106,107,105.5,113.5,115.5,114,115,116.5,115,118,117,118.5,125,120,131.5,129,138,140,147,149,150,145,151.5,146.5,
141.5,144,146.5,152,160.5,170.5,169.5,165,160.5,162.5,173,187.5,195,198,196,201.5,198,211,226]})

4.6 W Firm AI Server Case

Figure 6

Stock Price : [50.1,48.5,48.45],[49.45,50.6,53.2],[52.7,53.6,56.1],[61.7,65,68],[66.3,66.7,69.4],[71.1,71,70.6],[68.6,68,73],[70.7,71.8,76.7],[80.2,80.2,78.4],[77.7,84.1,82.8],[79.6,78.7,83.6],[90.8,95.7,105],[102.5,105.5,106],[103,113,124],[132,142,139.5],[133,128,134.5]

4.6 Q Firm vs. W Firm Correlation Comparison

Item	**Correlation Coefficient**	positive correlation angle	XAI SHAP mid-term feature strength	PCA Data Analysis pca=PCA(n_components=2)	Mutual Leader	NLP Sentiment Analysis	Trend scatter plot consistent	PCA Main Item	Cycle Position
W Firm	**0.9232222**	30 Degree	W>Q	array([0.99153649, 0.0062527])	W>Q Or Q>W	(Financial News Reviews A 2023/07/12 Score= p_pos=0.9970158775707659 (Financial News Reviews B) 2023/07/12 Score= p_pos=0.9999732808221131	High	DGX HGX Baseboard, Motherboard Design & System Integration main supplie	Start
Q Firm	**0.92558793**	30 Degree	W>Q	array([0.98751766, 0.00965384]) Comments:W>Q	W>Q Or Q>W	(Financial News Reviews A 2023/07/25 Score= p_pos=0.9604135182388435 (Financial News Reviews B) 2023/07/25 Score= p_pos=0.9972570277477952	High	DGX HGX assemble main supplier	Start

Table 1

Comments:

1. According to XAI SHAP analysis, N Firm has the characteristics of leadership (red visual features are obvious), and W Firm follows.

2. Empirical results: Nvidia Firm is highly correlated with W Firm.

3. Nvidia is good, and its representative exclusive supply chain companies will be good too.

4. As an exclusive supply chain enterprise, the correlation coefficient is higher than that of N Firm, indicating that the downstream reaction is stronger(catch up).

5. have crossed the "chasm".

5. Discussion

5.1. Consistency

(Financial News Reviews A)

Sentiment(classification='pos', p_pos=0.9132790148342463, p_neg=0.08672098516576003)

(Financial News Reviews B)

Sentiment(classification='pos', p_pos=0.9999967748992359, p_neg=3.22510076807198e-06)

Comments: Two financial news reports, the scores are consistent after analysis. for positive and 0.9 points. Indicates that the AI computer agrees with this trend. positive thinking, positive meaning.

5.2. Relationship

print(A_doc.similarity(B_doc))

0.8107878958004379

Comments: The two news articles are highly correlated. Indicates that the AI computer agrees with this trend.

5.3. Word Frequency Maps Generated by Financial News Reviews , Article A and Article B(Nvidia News)

(Figure 2)

fdist.most_common(30)

Out[64]: [(',', 10), ('and', 6), ('has', 4), ('technology', 4), ('in', 4), ('the', 4), ('AI', 3), ('.', 3), ('of', 3), ('a', 3),
('for', 3), ('have', 2), ('this', 2), ('wave', 2), ('graphics', 2), ('Nvidia', 2), ('as', 2), ('new', 2), ('been', 2),
('The', 1), ('global', 1), ('(', 1), ('Artificial', 1), ('Intelligence', 1), (')', 1), ('war', 1), ('begun', 1), ('various', 1),
('giants', 1), ('continuously', 1)]

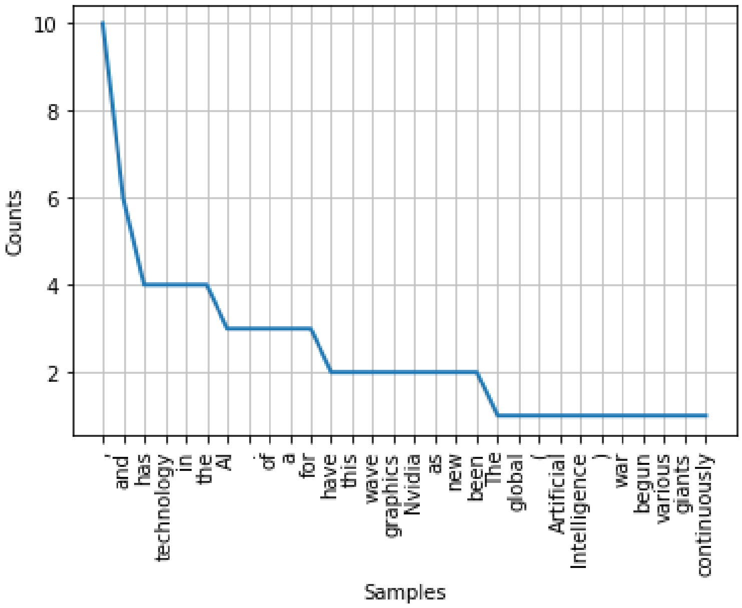


Figure 7

Feature comments: The stock price has an opportunity to break through (Figure 7)

5.4 Random Forest Prediction(Nvidia)

```
from sklearn.ensemble import RandomForestClassifier

import numpy as np

x=np.array([[14859],[16899],[17839],[20365],[21100],[21265],[21388],[23286],[23890],[22965],[25725],[27191]])

y=np.array(['up','up','up','up','up','up','up','up','up','up','up','up'])


RForest=RandomForestClassifier(n_estimators=10000,
max_depth=1000,random_state=0)


RForest.fit(x, y)
Out[44]: RandomForestClassifier(max_depth=1000, n_estimators=10000,
random_state=0)

print(RForest.predict([[40000]]))
['up']
```

5.5 Q Firm SHAP Analysis (48 day stock price)

```
pip install shap

import shap
```

from sklearn.ensemble import RandomForestClassifier

import numpy as np

x=np.array([[976],[1010],[1005],[1025],[1090],[1060],[1070],[1055],[1135],[1155],[1140],[1150],[1165],[1150],[1180],[1170],[1185],[1250],[1200],[1315],[1290],[1380],[1400],[1470],[1490],[1500],[1450],[1515],[1465],[1415],[1440],[1465],[1520],[1605],[1705],[1695],[1650],[1605],[1625],[1730],[1875],[1950],[1980],[1960],[2015],[1980],[2110],[2260]])

y=np.array(['up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up'])

RForest=RandomForestClassifier(n_estimators=100,
max_depth=10,random_state=2)

RForest.fit(x, y)
Out[8]: RandomForestClassifier(max_depth=10, random_state=2)

explainer=shap.TreeExplainer(RForest)

shap_values=explainer.shap_values(x)

shap.summary_plot(shap_values, x)

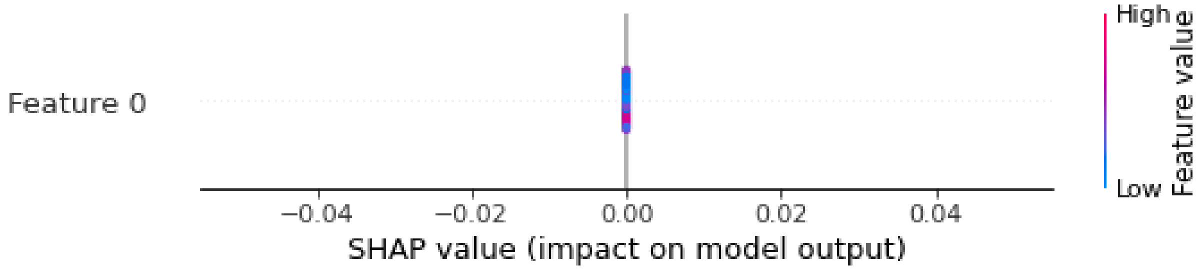


Figure 8

5.6 W Firm Shap analysis

```
pip install shap

import shap

from sklearn.ensemble import RandomForestClassifier

import numpy as np

x=np.array([[5010],[4850],[4845],[4945],[5060],[5320],[5270],[5360],[5610],[6170],[6500],[6800],[6630],[6670],[6940],[7110],[7100],[7060],[6860],[6800],[7300],[7070],[7180],[7670],[8020],[8020],[7840],[7770],[8410],[8280],[7960],[7870],[8360],[9080],[9570],[10500],[10250],[10550],[10600]])

y=np.array(['up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up','up'])


RForest=RandomForestClassifier(n_estimators=100,
max_depth=10,random_state=2)

RForest.fit(x, y)
Out[9]: RandomForestClassifier(max_depth=10, random_state=2)

explainer=shap.TreeExplainer(RForest)

shap_values=explainer.shap_values(x)

shap.summary_plot(shap_values, x)
```

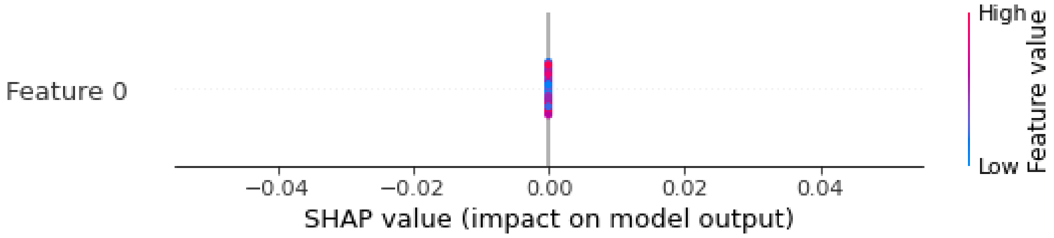


Figure 9

5.7 N Firm Correlation Coefficient

import numpy as np

import matplotlib.pyplot as plt

date=np.array([102, 109, 116, 123, 130, 206, 213, 220, 227, 306, 313,320])

price=np.array([148.59,168.99,178.39,203.65,211.00,212.65,213.88,232.86,238.90,229.65,257.25,271.91])

plt.scatter(date,price)
Out[61]: <matplotlib.collections.PathCollection at 0x214eeab1c10>

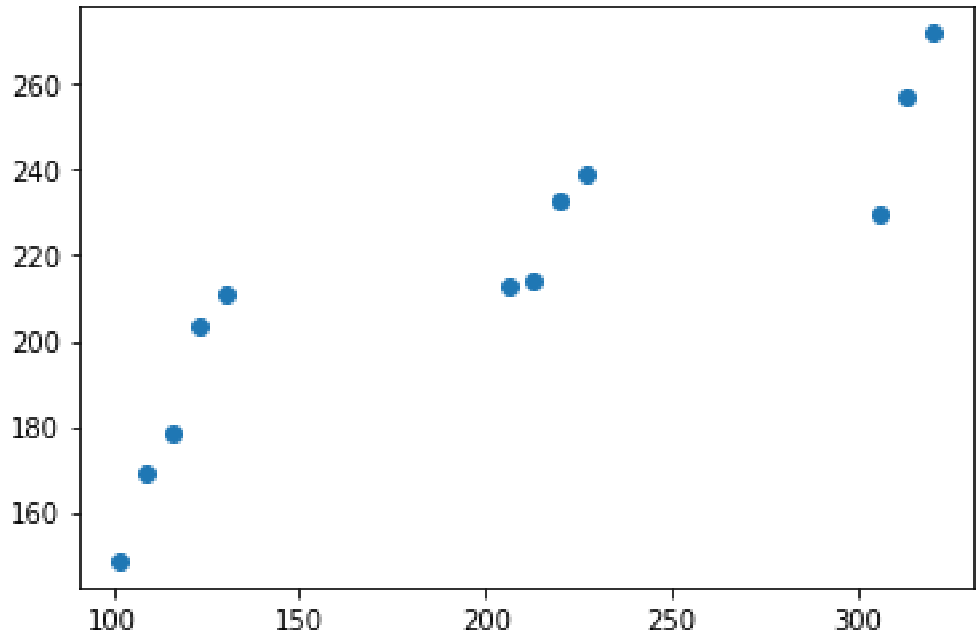


Figure 10

```
print(np.corrcoef(date,price))
[[1.         0.88897126]
 [0.88897126 1.        ]]
```

```
plt.plot(date,reg_model(date),color='red')
Out[69]: [<matplotlib.lines.Line2D at 0x214f1c17250>]
```

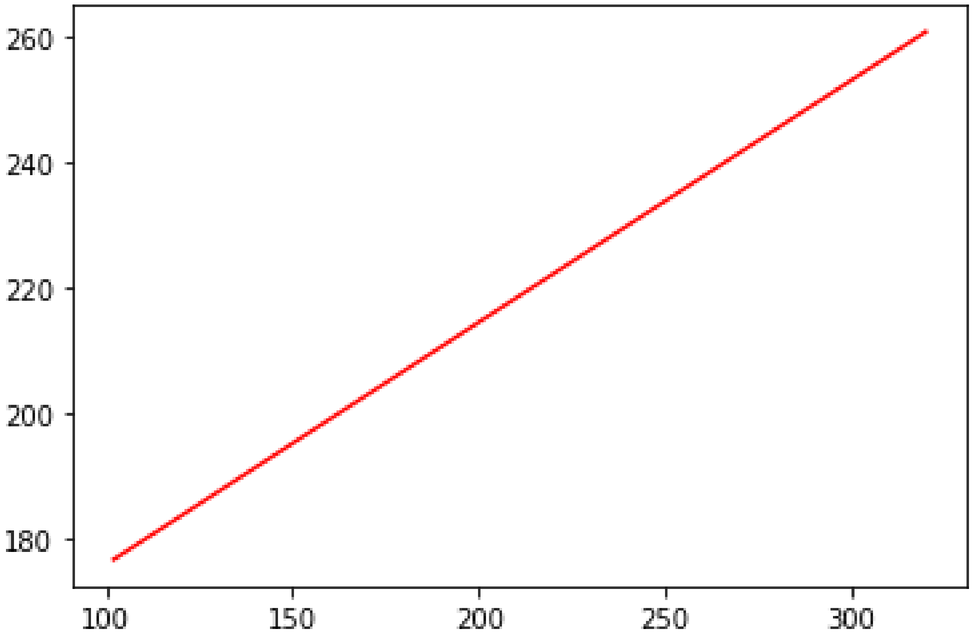


Figure 11

Remarks: Correlation coefficient=0.88897126, The red trend line is judged by the computer

5.8 Q Firm Correlation Coefficient

```
import numpy as np

import matplotlib.pyplot as plt
```

date=np.array([512,515,516,517,518,519,522,523,524,525,526,529,530,531,601,602,605,606,607,608,609,612,613,614,615,616,619,620,621,626,627,628,629,630,703,704,705,706,707,710,711,712,713,714,717,718,719,720,721])

price=np.array([101.5,97.6,101,100.5,102.5,109,106,107,105.5,113.5,115.5,114,115,116.5,115,118,117,118.5,125,120,131.5,129,138,140,147,149,150,145,151.5,146.5,141.5,144,146.5,152,160.5,170.5,169.5,165,160.5,162.5,173,187.5,195,198,196,201.5,198,211,226])

plt.scatter(date,price)
Out[5]: <matplotlib.collections.PathCollection at 0x1e799fccee0>

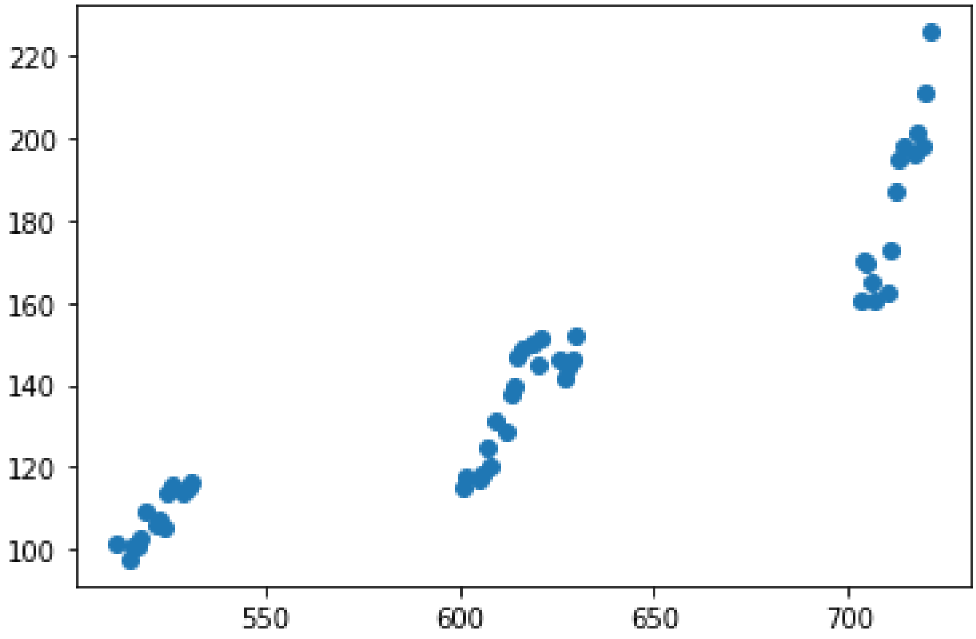


Figure 12

print(np.corrcoef(date,price))
[[1.   0.92558793]
 [0.92558793 1.   ]]

5.9 W Firm Correlation Coefficient

```
import numpy as np

import matplotlib.pyplot as plt

date=np.array([512,515,516,517,518,519,522,523,524,525,526,529,530,531,601,602,
605,606,607,608,609,612,613,614,615,616,619,620,621,626,627,628,629,630,703,70
4,705,706,707,710,711,712,713,714,717,718,719,720,721])

price=np.array([50.1,48.5,48.45,49.45,50.6,53.2,52.7,53.6,56.1,61.7,65,68,66.3,66.7,6
9.4,71.1,71,70.6,68.6,68,73,70.7,71.8,76.7,80.2,80.2,78.4,77.7,84.1,82.8,
79.6,78.7,83.6,90.8,95.7,105,102.5,105.5,106,103,113,124,132,142,139.5,133,128,13
4.5,147.5])

plt.scatter(date,price)
```

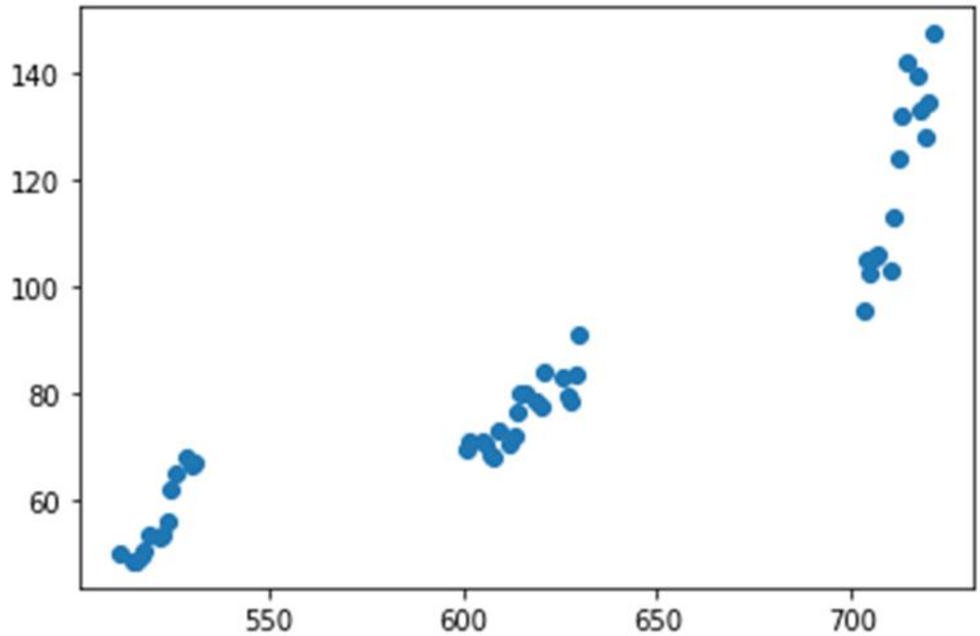


Figure 13

```
print(np.corrcoef(date,price))
[[1.         0.9232222]
 [0.9232222 1.        ]]
```

5.10 N Firm PCA analysis

```
import numpy as np

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

points=np.array([[148.59,168.99,178.39],[203.65,211.00,212.65],[213.88,232.86,238.90],[229.65,257.25,271.91]])

spoints=StandardScaler().fit_transform(points)

pca=PCA(n_components=2)

pcaComponents=pca.fit_transform(spoints)

import matplotlib.pyplot as plt

plt.legend(loc='upper right')
No handles with labels found to put in legend.
Out[133]: <matplotlib.legend.Legend at 0x214f2ba4580>

pca.explained_variance_ratio_
Out[134]: array([0.97916814, 0.02071121])
```

5.11 Q Firm PCA analysis

```
import numpy as np

from sklearn.preprocessing import StandardScaler
```

```
from sklearn.decomposition import PCA


points=np.array([[101.5,97.6,101],[100.5,102.5,109],[106,107,105.5],[113.5,115.5,114],[115,116.5,115],[118,117,118.5],[125,120,131.5],[129,138,140],[147,149,150],[145,151.5,146.5],
[141.5,144,146.5],[152,160.5,170.5],[169.5,165,160.5],[162.5,173,187.5],[195,198,196],[201.5,198,211]])

spoints=StandardScaler().fit_transform(points)

pca=PCA(n_components=2)

pcaComponents=pca.fit_transform(spoints)

import matplotlib.pyplot as plt

plt.legend(loc='upper right')
No handles with labels found to put in legend.
Out[41]: <matplotlib.legend.Legend at 0x2334773aaf0>

pca.explained_variance_ratio_
Out[10]: array([0.98751766, 0.00965384])
```

5.12 W Firm PCA

```
import numpy as np

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

points=np.array([   [50.1,48.5,48.45],[49.45,50.6,53.2],[52.7,53.6,56.1],[61.7,65,68],[66.3,66.7,69.4],[71.1,71,70.6],[68.6,68,73],[70.7,71.8,76.7],[80.2,80.2,78.4],[77.7,84.1,82.8],
```

[79.6,78.7,83.6],[90.8,95.7,105],[102.5,105.5,106],[103,113,124],[132,142,139.5],[133,128,134.5]])

spoints=StandardScaler().fit_transform(points)

pca=PCA(n_components=2)

pcaComponents=pca.fit_transform(spoints)

import matplotlib.pyplot as plt

plt.legend(loc='upper right')

pca.explained_variance_ratio_
Out[10]: array([0.99153649, 0.0062527])

5.13 The stock prices of the two companies are highly consistent(scatter)

Q
Firm=np.random.normal([[976],[1010],[1005],[1025],[1090],[1060],[1070],[1055],[1135],[1155],[1140],[1150],[1165],[1150],[1180],[1170],[1185],[1250],[1200],[1315],[1290],[1380],[1400],
[1470],[1490],[1500],[1450],[1515],[1465],[1415],[1440],[1465],[1520],[1605],[1705],[1695],[1650],[1605],[1625],[1730],[1875],[1950],[1980],[1960],[2015],[1980],[2110],[2260]])

W
Firm=np.random.normal([[5010],[4850],[4845],[4945],[5060],[5320],[5270],[5360],[5610],[6170],[6500],[6800],[6630],[6670],[6940],[7110],[7100],[7060],[6860],[6800],[7300],[7070],
[7180],[7670],[8020],[8020],[7840],[7770],[8410],[8280],[7960],[7870],[8360],[9080],[9570],[10500],[10250],[10550],[10600],[10300],[11300],[12400],[13200],[14200],[13950],[13300],[12800],[13450]])

scatter(Q Firm, W Firm)

Out[23]: <matplotlib.collections.PathCollection at 0x250b138e760>

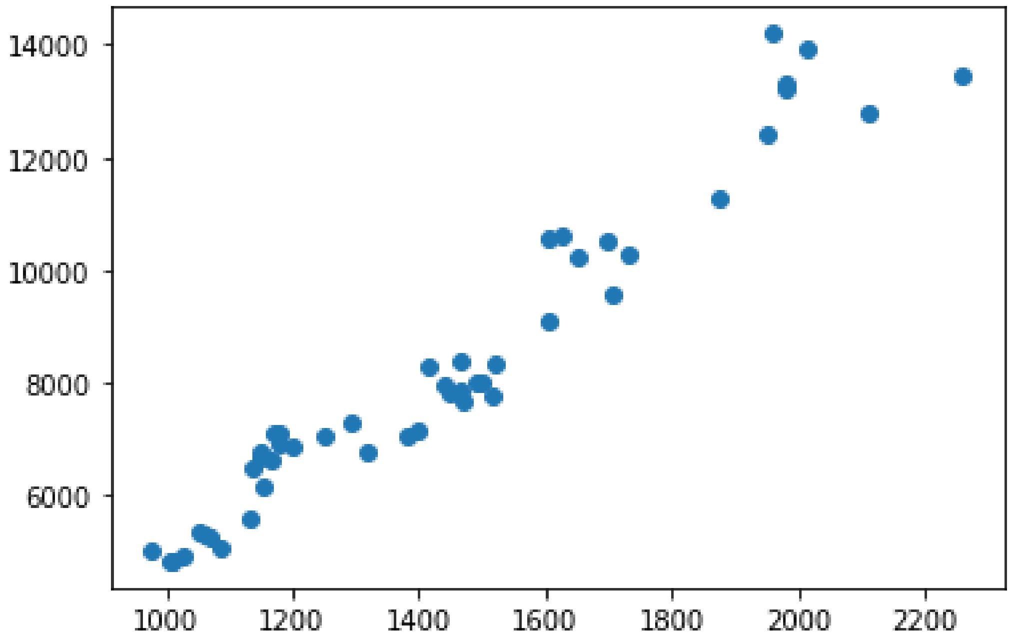


Figure 14

5.14 AI Server Firm

Evaluation Principles:

1. Long arrangement
2. The trend of positive correlation
3. High correlation coefficient

6. Conclusions

Bayesian inference is a powerful supervised learning theory that can be used for object classification. It can calculate the probability of classification using any continuous number or category-scale data, and it has a wide range of applications.The goal of this research is to utilize natural language processing, natural language understanding, and similarity technology in AI to analyze financial news for predictive purposes.

The NaiveBayesAnalyzer was used to collect project data, capture essential text and data for analysis, and the results showed the following, A: Sentiment-classification= 'pos', p_pos0.9132790148342463=, p_neg= 0.08672098516576003; B: Sentiment-classification= 'pos', p_pos=0.9999967748992359,p_neg=3.22510076807198e-06 . The scores obtained after analyzing two financial news reports were consistent, indicating a positive trend with a score of 0.9. This suggests that the AI computer agrees with this positive sentiment.Furthermore, the similarity and correlation between A_doc and B_doc was calculated, with a score of 0.81 indicating that the two news articles are highly correlated. Word frequency graph analysis also revealed some key features. Naive Bayesian inference considers each variable as independent and derives the "naive Bayesian inference." This theory and technology can provide extremely accurate analysis results, making it an efficient AI calculation.This research successfully estimated the trend and significance of financial news. This method can be employed in the field of NLP and XAI to obtain more intelligent text quantification and analysis. The NaiveBayesAnalyzer can automatically draw conclusions, while Random Forest can be used for trend forecasting. I did a research in March, and then verified it again at the end of May. Indeed in line with the mid-March forecast. Accuracy = 100%.(Nvidia Stock Price>400)

The paradigm shift will accelerate the development of AI electronic technology. and generate a powerful AI hardware supply chain. Rapid Innovation Diffusion Effect: AIGC→GPU→GPU Board →AI Server→Cooler→ABF→AI power supply→Chassis.The trend of representing companies in AI Server is highly positively correlated.

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